

# Structured learning of metric ensembles with application to person re-identification

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## Abstract

Matching individuals across non-overlapping camera networks, known as person re-identification, is a fundamentally challenging problem due to the large visual appearance changes caused by variations of viewpoints, lighting, and occlusion. Approaches in literature can be categorized into two streams: The first stream is to develop reliable features against realistic conditions by combining several visual features in a pre-defined way; the second stream is to learn a metric from training data to ensure strong inter-class differences and intra-class similarities. However, seeking an optimal combination of visual features which is generic yet adaptive to different benchmarks is an unsolved problem, and metric learning models easily get over-fitted due to the scarcity of training data in person re-identification. In this paper, we propose two effective structured learning based approaches which explore the adaptive effects of visual features in recognizing persons in different benchmark data sets. Our framework is built on the basis of multiple low-level visual features with an optimal ensemble of their metrics. We formulate two optimization algorithms, CMC<sup>triplet</sup> and CMC<sup>top</sup>, which directly optimize evaluation measures commonly used in person re-identification, also known as the Cumulative Matching Characteristic (CMC) curve. The more standard CMC<sup>triplet</sup> formulation works on the triplet information by maximizing the relative distance between a matched pair and a mismatched pair in each triplet unit. The CMC<sup>top</sup> formulation, modeled on a structured learning of maximizing the correct identification among top candidates, is demonstrated to be more beneficial to person re-identification by directly optimizing an objective closer to the actual testing criteria. The combination of these factors leads to a person re-identification system which outperforms most existing algorithms. More importantly, we advance state-of-the-art results by improving the rank-1 recognition rates from 40% to 61% on the iLIDS benchmark, 16% to 22% on the PRID2011 benchmark, 43% to 50% on the VIPeR benchmark, 34% to 55% on the CUHK01 benchmark and 21% to 68% on the CUHK03 benchmark.

**Keywords:** Person re-identification, Learning to rank, Metric ensembles, Structured learning.

## 1. Introduction

The task of person re-identification (re-id) is to match pedestrian images observed from different and disjoint camera views. Despite extensive research efforts in re-id [9, 36, 48, 51, 44, 47, 33, 20, 46], the problem itself is still a very challenging task due to (a) large variation in visual appearance (person's appearance often undergoes large variations across different camera views); (b) significant changes in human poses at the time the image was captured; (c) large amount of illumination changes, background clutter and occlusions; d) relatively low resolution and the different placement of the cameras. Moreover, the problem becomes increasingly difficult when there are high variations in pose, camera viewpoints, and illumination, etc.

To address these challenges, existing research has concentrated on the development of sophisticated and robust features to describe visual appearance under significant changes. Most of them use appearance-based features that are viewpoint invariant such as color and texture descriptors [7, 9, 11, 39, 23]. However, the system that relies heavily on one specific type of visual cues, e.g., color, texture or shape, would not be practical

and powerful enough to discriminate individuals with similar visual appearance. Some studies have tried to address the above problem by seeking a combination of robust and distinctive feature representation of person's appearance, ranging from color histogram [11], spatial co-occurrence representation [39], LBP [44], to color SIFT [47]. The basic idea of exploiting multiple visual features is to build an ensemble of metrics (distance functions), in which each distance function is learned using a single feature and the final distance is calculated from a weighted sum of these distance functions [7, 44, 47]. These works often pre-define distance weights, which need to be re-estimated beforehand for different data sets. However, such a pre-defined principle has some drawbacks.

- Different real-world re-id scenarios can have very different characteristics, e.g., variation in view angle, lighting and occlusion. Simply combining multiple distance functions using pre-determined weights may be undesirable as highly discriminative features in one environment might become irrelevant in another environment.
- The effectiveness of distance learning heavily relies on the quality of the feature selected, and such selection requires some domain knowledge and expertise.
- Given that certain features are determined to be more re-

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liable than others under a certain condition, applying a standard distance measure for each individual match is undesirable as it treats all features equally without differentiation on features.

In these ends, it necessarily demands a principled approach that is able to automatically select and learn weights for diverse metrics, meanwhile generic yet adaptive to different scenarios.

Person re-identification problem can also be cast as a learning problem in which either metrics or discriminative models are learned [4, 5, 16, 17, 42, 43, 44, 20, 41, 27, 49], which typically learn a distance measure by minimizing intra-class distance and maximizing inter-class distance simultaneously. Thereby, they require sufficient labeled training data from each class<sup>1</sup> and most of them also require new training data when camera settings change. Nonetheless, in person re-id benchmark, available training data is relatively scarce, and thus inherently undersampled for building a representative class distribution. This intrinsic characteristic of person re-id problem makes metric learning pipelines easily overfitted and unable to be applicable in small image sets.

To combat above difficulties simultaneously, in this paper, we introduce two structured learning based approaches to person re-id by learning weights of distance functions for low-level features. The first approach,  $\text{CMC}^{\text{triplet}}$ , optimizes the relative distance using the triplet units, each of which contains three person images, i.e., one person with a matched reference and a mismatched reference. Treating these triplet units as input, we formulate a large margin framework with triplet loss where the relative distance between the matched pair and the mismatched pair tends to be maximized. An illustration of  $\text{CMC}^{\text{triplet}}$  is shown in Fig. 1. This triplet based model is more natural for person re-id mainly because the intra-class and inter-class variation may vary significantly for different classes, making it inappropriate to require the distance between a matched/mismatched pair to fall within an absolute range [49]. Also, training images in person re-id are relatively scarce, whereas the triplet-based training model is to make comparison between any two data points rather than comparison between any data distribution boundaries or among clusters of data. This thus alleviates the over-fitting problem in person re-id given undersampled data. The second approach,  $\text{CMC}^{\text{top}}$ , is developed to maximize the average rank- $k$  recognition rate, in which  $k$  is chosen to be small, e.g.,  $k < 10$ . Setting the value of  $k$  to be small is crucial for many real-world applications since most surveillance operators typically inspect only the first ten or twenty items retrieved. Thus, we directly optimize the testing performance measure commonly used in CMC curve, i.e., the recognition rate at rank- $k$  by using structured learning.

The main contributions of this paper are three-fold:

- We propose two principled approaches,  $\text{CMC}^{\text{triplet}}$  and  $\text{CMC}^{\text{top}}$ , to build an ensemble of person re-id metrics. The standard approach  $\text{CMC}^{\text{triplet}}$  is developed based on triplet information, which is more tolerant to large intra

and inter-class variations, and alleviate the over-fitting problem. The second approach of  $\text{CMC}^{\text{top}}$  directly optimizes an objective closer to the testing criteria by maximizing the correctness among top  $k$  matches using structured learning, which is empirically demonstrated to be more beneficial to improving recognition rates.

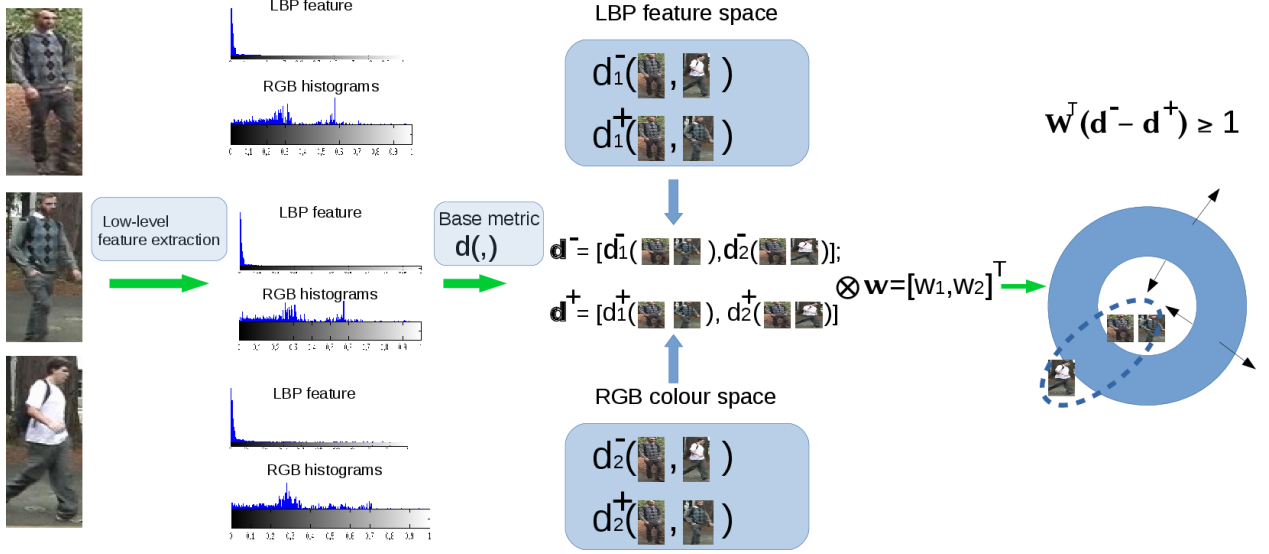
- We perform feature quantification by exploring the effects of diverse feature descriptors in recognizing persons in different benchmarks. An ensemble of metrics is formulated into a late fusion paradigm where a set of weights corresponding to visual features are automatically learned. This late fusion scheme is empirically studied to be superior to various early fusions on visual features.
- Extensive experiments are carried out to demonstrate that by building an ensemble of person re-id metrics learned from different visual features, notable improvement on rank-1 recognition rate can be obtained. In addition, our ensemble approaches are highly flexible and can be combined with linear and non-linear metrics. For non-linear base metrics, we extend our approaches to be tractable and suitable to large-scale benchmark data sets by approximating the kernel learning.

## 2. Related Work

Many person re-id approaches are proposed to seek robust and discriminative features such that they can be used to describe the appearance of the same individual across different camera views under various changes and conditions [2, 3, 7, 9, 11, 19, 39, 47, 48]. For instance, Bazzani *et al.* represent a person by a global mean color histogram and recurrent local patterns through epitomic analysis [2]. Farenzena *et al.* propose the symmetry-driven accumulation of local features (SDALF) which exploits both symmetry and asymmetry, and represents each part of a person by a weighted color histogram, maximally stable color regions and texture information [7]. Gray and Tao introduce an ensemble of local features which combines three color channels with 19 texture channels [11]. Schwartz and Davis propose a discriminative appearance based model using partial least squares where multiple visual features: texture, gradient and color features are combined [38]. Zhao *et al.* combine dcolorSIFT with unsupervised salience learning to improve its discriminative power in person re-id [47] (eSDC), and further integrate both salience matching and patch matching into a unified RankSVM framework (SalMatch [46]). They also propose mid-level filters (MidLevel) for person re-identification by exploring the partial area under the ROC curve (pAUC) score [48]. Lisanti *et al.* [22] leverage low-level feature descriptors to approximate the appearance variants in order to discriminate individuals by using sparse linear reconstruction model (ISR).

Another line to approach the problem of matching people across cameras is to essentially formalize person re-id as a supervised metric/distance learning where a projection matrix is sought out so that the projected Mahalanobis-like distance is

<sup>1</sup>Images of each person in a training set form a class.



**Figure 1:** An illustration of our triplet-based framework. Given a set of triplets, our model is trained to fully exploit low-level features by adaptively learning weights for their distance functions, so as to maximize the relative distance between the matched pair and the mismatched pair for each triplet.

small when feature vectors represent the same person and large otherwise. Along this line, a large number of metric learning and ranking algorithms have been proposed [4, 12, 5, 33, 16, 17, 41, 42, 43, 44, 20, 27, 49]. Among these Mahalanobis distance learning algorithms, the Large Margin Nearest Neighbor Learning (LMNN) [41], Information Theoretic Metric Learning (ITML) [5], and Logistic Discriminant Metric Learning (LDML) [12] are three representative methods.

Metric learning methods can be applied to person re-id to achieve the state of the art results [14, 17, 20]. In particular, Koestinger *et al.* propose the large-scale metric learning from equivalence constraint (KISSME) which considers a log likelihood ratio test of two Gaussian distributions [17]. Li *et al.* propose the learning of locally adaptive decision functions (LADF) [20]. An alternative approach is to use a logistic function to approximate the hinge loss so that the global optimum still can be achieved by iteratively gradient search along the projection matrix as in PCCA [27], PRDC [49] and Cross-view Quadratic Discriminant Analysis (XQDA) [21]. However, these methods are prone to over-fitting and can result in poor classification performance due to large variations among samples. We approach this problem by proposing a more generic algorithm which is developed based on triplet information so as to generate more constraints for distance learning, and thus mitigate the over-fitting issue. Prosser *et al.* use pairs of similar and dissimilar images and train the ensemble RankSVM such that the true match gets the highest rank [34]. However, the model of RankSVM needs to determine the weight between the margin function and the ranking error cost function, which is computationally costly. Wu *et al.* applies the Metric Learning to Rank (MLR) method of [26] to person re-id [43].

Although a large number of existing algorithms have exploited state-of-the-art visual features and advanced metric learning algorithms, we observe that the best obtained overall perfor-

mance on commonly evaluated person re-id benchmarks, e.g., iLIDS and VIPeR, is still far from the performance needed for most real-world surveillance applications. The goal of this paper is to show how one can carefully design a standard, generalized person re-id framework to achieve state-of-the-art results on person re-id testing data sets. Preliminary results of this work were published in [31].

### 3. Notations and Problem Definition

Throughout the paper, we denote vectors with bolded font and matrices with capital letters. We focus on the single-shot modality where there is a single exemplar for each person in the gallery and one exemplar for each person in the probe set. We represent a set of training samples by  $\{(x_i, x_i^+)\}_{i=1}^m$  where  $x_i \in \mathbb{R}^D$  represents a training example from one camera,  $x_i^+$  is the corresponding image of the same person from a different camera, and  $m$  is the number of persons in the training data. Then, a set of triplets for each sample  $x_i$  can be generated as  $\{(x_i, x_i^+, x_{i,j}^-)\}$  for  $i = 1, \dots, m$  and  $i \neq j$ . Here we introduce  $x_{i,j}^- \in X_i^-$  where  $X_i^-$  denotes a subset of images of persons with a different identity to  $x_i$  from a different camera view. We assume that there exist a set of distance functions  $d_i(\cdot, \cdot)$  which calculate the distance between two given inputs. Our goal is to learn a weighted distance function:  $d(\cdot, \cdot) = \sum_{i=1}^T w_i d_i(\cdot, \cdot)$ , such that the distance between  $x_i$  and  $x_i^+$  is smaller than the distance between  $x_i$  and any  $x_{i,j}^-$ . A good distance function can facilitate the cumulative matching characteristic (CMC) curve to approach one faster.

### 4. Our Approach

In this section, two structured learning based approaches are presented to learn an ensemble of base metrics. We then

discuss base metrics that will be used in our experiment as well as a strategy of approximating non-linear metric learning for the case of large-sized person re-id data set.

#### 4.1. Ensemble of base metrics

We propose two different approaches to learn an ensemble of base metrics in an attempt to rank the possible candidates such that the highest ranked candidate is the correct match for a query image. In our setting, we consider the most commonly used performance measure for evaluating person re-id, cumulative matching characteristic (CMC) curve [10], which represents results of an identification task by plotting the probability of correct identification against the number of candidates returned. A better person re-id algorithm can make the CMC curve approach one faster. Achieving the best rank-1 recognition rate is the ultimate goal [48] in many real-world surveillance applications because most users are more likely to consider the first a few returned candidates. Thus, our goal is to improve the recognition rate among the  $k$  best candidates with a minimized  $k$ , e.g.,  $k < 20$ . The first approach,  $\text{CMC}^{\text{triplet}}$ , aims at minimizing the number of returned list of candidates in order to achieve a perfect identification, i.e., minimizing  $k$  such that the rank- $k$  recognition rate is equal to one. The second approach,  $\text{CMC}^{\text{top}}$ , optimizes the probability that any of these  $k$  best matches are correct.

#### 4.2. Relative distance based approach ( $\text{CMC}^{\text{triplet}}$ )

The  $\text{CMC}^{\text{triplet}}$  approach aims to optimize the rank- $k$  recognition rate of the candidate list for a given probe image. To do this, we propose to learn an ensemble of distance functions based on relative comparison of triplets [37]. The relative distance relationship is reflected by a set of triplet units  $\{(\mathbf{x}_i, \mathbf{x}_i^+, \mathbf{x}_{i,j}^-)\}_{i,j}$ . For an image  $\mathbf{x}_i$  of a person, we wish to learn a re-id model to successfully identify another image  $\mathbf{x}_i^+$  of the same person captured by another camera view. For a triplet  $\{(\mathbf{x}_i, \mathbf{x}_i^+, \mathbf{x}_{i,j}^-)\}_{i,j}$ , we assume a distance satisfying  $d(\mathbf{x}_i, \mathbf{x}_{i,j}^-) > d(\mathbf{x}_i, \mathbf{x}_i^+)$ , where  $\mathbf{x}_{i,j}^-$  is an image of any other person except  $\mathbf{x}_i$ . Inspired by the large margin framework with the hinge loss, a large margin is expected to exist between positive pairs and negative pairs, that is  $d(\mathbf{x}_i, \mathbf{x}_{i,j}^-) \geq 1 + d(\mathbf{x}_i, \mathbf{x}_i^+)$ . Considering this margin condition cannot be satisfied by all triplets, we introduce a slack variable to enable soft margin. Finally, by generalizing this inequality to the entire training set, the primal problem that we want to optimize is

$$\begin{aligned} \min_{\mathbf{w}, \xi} \quad & \frac{1}{2} \|\mathbf{w}\|_2^2 + \nu \frac{1}{m(m-1)} \sum_{i=1}^m \sum_{j=1}^{m-1} \xi_{ij} \\ \text{s.t.} \quad & \mathbf{w}^\top (\mathbf{d}_j^- - \mathbf{d}_i^+) \geq 1 - \xi_{ij}; \mathbf{w} \geq 0; \xi \geq 0. \end{aligned} \quad (1)$$

Here  $\mathbf{w}$  is the vector of the base metric weights,  $m$  denotes the total number of identities in the training set.  $\nu > 0$  is the regularization parameter and  $\mathbf{d}_j^- = [d_1(\mathbf{x}_i, \mathbf{x}_{i,j}^-), \dots, d_t(\mathbf{x}_i, \mathbf{x}_{i,j}^-)]$ ,  $\mathbf{d}_i^+ = [d_1(\mathbf{x}_i, \mathbf{x}_i^+), \dots, d_t(\mathbf{x}_i, \mathbf{x}_i^+)]$  and  $\{d_1(\cdot, \cdot), \dots, d_t(\cdot, \cdot)\}$  represent a set of base metrics. The regularization term  $\|\mathbf{w}\|_2^2$  is introduced to avoid the trivial solution of arbitrarily large  $\mathbf{w}$ . It can be seen

that the number of constraints in (1) is quadratic in terms of the size of training examples, and directly solving (1) using off-the-shelf optimization toolboxes is intractable. To address this issue, we present an equivalent reformulation of (1), which can be efficiently solved in a linear runtime using the cutting-plane algorithm. We first reformulate (1) to be:

$$\begin{aligned} \min_{\mathbf{w}, \xi} \quad & \frac{1}{2} \|\mathbf{w}\|_2^2 + \nu \xi \\ \text{s.t.} \quad & \frac{1}{m(m-1)} \mathbf{w}^\top \left[ \sum_{i=1}^m \sum_{j=1}^{m-1} (\mathbf{d}_j^- - \mathbf{d}_i^+) \right] \geq 1 - \xi; \mathbf{w} \geq 0; \xi \geq 0. \end{aligned} \quad (2)$$

This new formulation has a single slack variable and later on we show the cutting-plane method can be applied to solve it.

#### 4.3. Top recognition at rank- $k$ ( $\text{CMC}^{\text{top}}$ )

In  $\text{CMC}^{\text{triplet}}$ , we set up the hypothesis that for any triplet, images belonging to the same identity should be closer than images from different identities. Our second formulation is motivated by the fact that person re-id users often concentrate on only the first few retrieved matches. Bearing this in mind, we propose  $\text{CMC}^{\text{top}}$  with an objective of maximizing the correct identification among the top  $k$  best candidates. Specifically, we directly optimize the performance measure indicated by the CMC curve (recognition rate at rank- $k$ ) by taking advantage of structured learning framework [15, 29]. The main difference between our work and [29] lies in the fact that [29] attempts to rank all positive samples before a subset of negative samples while our works attempt to rank a pair of the same individual above a pair of different individuals. Given a training identity  $\mathbf{x}_i$  and its correct match  $\mathbf{x}_i^+$  from a different view, the relative ordering of all matching candidates in different view can be represented via a vector  $\mathbf{p} \in \mathbb{R}^{m'}$ , in which  $p_j$  is 0 if  $\mathbf{x}_i^+$  is ranked *above*  $\mathbf{x}_{i,j}^-$  and 1 if  $\mathbf{x}_i^+$  is ranked *below*  $\mathbf{x}_{i,j}^-$ . Here  $m'$  indicates the total number of identities who has a different identity to  $\mathbf{x}_i$ . Since there exists only one match of the same identity,  $m'$  is equal to  $m - 1$ . We can generalize this idea to the entire training set and represent the relative ordering via a matrix  $\mathbf{P} \in \{0, 1\}^{m \times m'}$  as follows:

$$p_{ij} = \begin{cases} 0 & \text{if } \mathbf{x}_i^+ \text{ is ranked above } \mathbf{x}_{i,j}^- \\ 1 & \text{otherwise.} \end{cases} \quad (3)$$

The correct relative ordering of  $\mathbf{P}$  can be defined as  $\mathbf{P}^*$  where  $p_{ij}^* = 0, \forall i, j$ . The loss among the top  $k$  candidates between  $\mathbf{P}^*$  and an arbitrary ordering  $\mathbf{P}$  can be formulated as,

$$\Delta(\mathbf{P}^*, \mathbf{P}) = \frac{1}{m \cdot k} \sum_{i=1}^m \sum_{j=1}^k p_{ij}, \quad (4)$$

where  $j$  denotes the index of the retrieved candidates ranked in the  $j$ -th position among all top  $k$  best candidates. We define the joint reward score,  $\psi$ , of the form:

$$\psi(\mathbf{S}, \mathbf{P}) = \frac{1}{m \cdot k} \sum_{i=1}^m \sum_{j=1}^k (1 - p_{ij})(\mathbf{d}_j^- - \mathbf{d}_i^+), \quad (5)$$

where  $S$  represent a set of triplets generated from the training data,  $\mathbf{d}_j^- = [d_1(\mathbf{x}_i, \mathbf{x}_{i,j}^-), \dots, d_t(\mathbf{x}_i, \mathbf{x}_{i,j}^-)]$  and  $\mathbf{d}_i^+ = [d_1(\mathbf{x}_i, \mathbf{x}_i^+), \dots, d_t(\mathbf{x}_i, \mathbf{x}_i^+)]$ . The intuition of Eq. (5) is to establish a structure consistency between relative distance margins and corresponding rankings in  $S$ . Specifically, the distance margin  $(\mathbf{d}_j^- - \mathbf{d}_i^+)$  is scaled proportionally to the loss in the resulting ordering  $(1 - p_{ij})$ . This can ensure a high reward score can be computed by Eq. (5) if postive and negative pairs exhibit large margins and meanwhile  $\mathbf{x}_i^+$  is always ranked *above*  $\mathbf{x}_{i,j}^-$  (i.e.,  $p_{ij} = 0, j = 1, \dots, k$ ). Thus,  $\psi(S, P)$  can be seen as a joint reward score to reflect the structure consistency between  $S$  and  $P$ .

In fact, the choice of  $\psi(S, P)$  is to guarantee that  $\mathbf{w}$ , which optimizes  $\mathbf{w}^\top \psi(S, P)$ , will also produce the distance function  $d(\cdot, \cdot) = \sum_{g=1}^t w_g d_g(\cdot, \cdot)$  that achieves the optimal average recognition rate among the top  $k$  candidates. The above problem can be summarized as the following convex optimization problem:

$$\min_{\mathbf{w}, \xi} \frac{1}{2} \|\mathbf{w}\|_2^2 + \nu \xi \quad (6)$$

s.t.  $\mathbf{w}^\top (\psi(S, P^*) - \psi(S, P)) \geq \Delta(P^*, P) - \xi; \forall P \geq 0; \xi \geq 0.$

The intuition of Eq (6) is to ensure there is a large margin  $(\Delta(P^*, P))$  between the reward score from the correct ordering  $\psi(S, P^*)$  and any estimated ordering  $\psi(S, P)$  with respect to  $S$ .

#### 4.3.1. Cutting-plane optimization

The optimization problems in (2) and (6) involve quadratic program, which is unable to be solved directly. Hence, we resort to cutting-plane method to approximate its solution. The cutting-plane optimization works by assuming that a small subset of the constraints are sufficient to find an  $\epsilon$ -approximate solution to the original problem. The algorithm begins with an empty initial constraint set and iteratively adds the most violated constraint set. At each iteration, it computes the solution over the current working set, finds the most violated constraint, and puts it into the working set. The algorithm continues until no constraint is violated by more than  $\epsilon$ . Since the quadratic program is of constant size, the cutting-plane method converges in a constant number of iterations. We present CMC<sup>top</sup> in Algorithm 1.

In CMC<sup>top</sup>, the optimization problem for finding the most violated constraint (Algorithm 1, step ②) can be written as,

$$\begin{aligned} \bar{P} &= \max_P \Delta(P^*, P) - \mathbf{w}^\top (\psi(S, P^*) - \psi(S, P)) \quad (7) \\ &= \max_P \Delta(P^*, P) - \frac{1}{mk} \sum_{i,j} p_{ij} \mathbf{w}^\top (\mathbf{d}_j^- - \mathbf{d}_i^+) \\ &= \max_P \sum_{i=1}^m \left( \sum_{j=1}^k p_{i,j} (1 - \mathbf{w}^\top \mathbf{d}_{i,j}^+) - \sum_{j=k+1}^{m'} p_{i,j} \mathbf{w}^\top \mathbf{d}_{i,j}^+ \right) \end{aligned}$$

where  $\mathbf{d}_{i,j}^\pm = \mathbf{d}_j^\pm - \mathbf{d}_i^\pm$ . Since  $p_{ij}$  in (7) is independent, the solution to (7) can be solved by maximizing over each element  $p_{ij}$ . Hence, in  $\bar{P}$  the most violated constraint corresponds to,

$$\bar{p}_{i,j} = \begin{cases} \frac{1}{2} (\mathbf{w}^\top (\mathbf{d}_j^- - \mathbf{d}_i^+) \leq 1), & \text{if } j \in \{1, \dots, k\} \\ \frac{1}{2} (\mathbf{w}^\top (\mathbf{d}_j^- - \mathbf{d}_i^+) \leq 0), & \text{otherwise.} \end{cases}$$

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#### Algorithm 1 Cutting-plane algorithm for solving CMC<sup>top</sup> (CMC<sup>triplet</sup>)

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**Input:**

- 1) A set of base metrics of the same identity and different identities  $\{\mathbf{d}_i^+, \mathbf{d}_j^-\}$ ;
- 2) The regularization parameter,  $\nu$ ;
- 3) The cutting-plane termination threshold,  $\epsilon$ ;

**Output:** The base metrics' coefficients  $\mathbf{w}$ ,

**Initialize:** The working set,  $C = \emptyset$ ;

$g(S, P, \mathbf{w}) = \Delta(P^*, P) - \frac{1}{mk} \sum_{i,j} p_{ij} \mathbf{w}^\top (\mathbf{d}_j^- - \mathbf{d}_i^+)$ ;

**Repeat**

- ① Solve the primal problem using linear SVM,

$$\min_{\mathbf{w}, \xi} \frac{1}{2} \|\mathbf{w}\|_2^2 + \nu \xi \quad \text{s.t. } g(S, P, \mathbf{w}) \leq \xi, \forall P \in C;$$

- ② Compute the most violated constraint,

$$\bar{P} = \max_P g(S, P, \mathbf{w});$$

- ③  $C \leftarrow C \cup \{\bar{P}\}$ ;

**Until**  $g(S, P, \mathbf{w}) \leq \xi + \epsilon$ ;

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For CMC<sup>triplet</sup>, one replaces  $g(S, P, \mathbf{w})$  in Algorithm 1 with  $g(S, \mathbf{w}) = 1 - \frac{1}{m(m-1)} \mathbf{w}^\top \left[ \sum_{i,j} (\mathbf{d}_j^- - \mathbf{d}_i^+) \right]$  and repeats the same procedure.

#### 4.4. Base metrics

In this paper, two types of base metrics are employed to develop our structured learning algorithms, which are KISS metric learning [17] and kernel Local Fisher Discriminant Analysis (kLFDA) [44].

*KISS metric learning revisit.* The KISS ML method learns a linear mapping by estimating a matrix  $\mathbf{M}$  such that the distance between images of the same individual,  $(\mathbf{x}_i - \mathbf{x}_i^+)^\top \mathbf{M} (\mathbf{x}_i - \mathbf{x}_i^+)$ , is less than the distance between images of different individuals,  $(\mathbf{x}_i - \mathbf{x}_{i,j}^-)^\top \mathbf{M} (\mathbf{x}_i - \mathbf{x}_{i,j}^-)$ . Specifically, it considers two independent generation processes for observed images of similar and dissimilar pairs. From a statistical view, the optimal statistical decision whether a pair  $(\mathbf{x}_i, \mathbf{x}_j)$  is dissimilar or not can be obtained by a likelihood ratio test. Thus, the likelihood ratio test between dissimilar pairs and similar pairs is,

$$r(\mathbf{x}_i, \mathbf{x}_j) = \log \frac{\frac{1}{\sqrt{2\pi|\Sigma_D|}} \exp(-\frac{1}{2} \mathbf{x}_{ij}^\top \Sigma_D^{-1} \mathbf{x}_{ij})}{\frac{1}{\sqrt{2\pi|\Sigma_S|}} \exp(-\frac{1}{2} \mathbf{x}_{ij}^\top \Sigma_S^{-1} \mathbf{x}_{ij})}, \quad (8)$$

where  $\mathbf{x}_{ij} = \mathbf{x}_i - \mathbf{x}_j$ ,  $\Sigma_D$  and  $\Sigma_S$  are covariance matrices of dissimilar pairs and similar pairs, respectively. By applying the Bayesian rule and the log-likelihood ratio test, the decision function can be simplified as  $f(\mathbf{x}_{ij}) = \mathbf{x}_{ij}^\top (\Sigma_S^{-1} - \Sigma_D^{-1}) \mathbf{x}_{ij}$ , and the derived distance function between  $\mathbf{x}_i$  and  $\mathbf{x}_j$  is

$$d(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i - \mathbf{x}_j)^\top (\Sigma_S^{-1} - \Sigma_D^{-1}) (\mathbf{x}_i - \mathbf{x}_j). \quad (9)$$

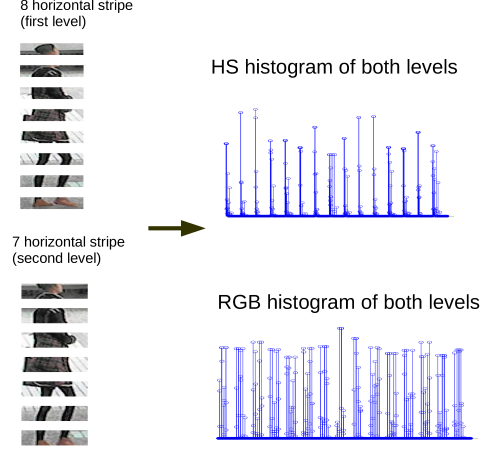
Hence, learning the distance function corresponds to estimating the covariant matrices  $\Sigma_S$  and  $\Sigma_D$ , and we have the Mahalanobis distance matrix  $\mathbf{M}$  as  $\mathbf{M} = \Sigma_S^{-1} - \Sigma_D^{-1}$ . In [17],  $\mathbf{M}$  is obtained by clipping the spectrum of  $\mathbf{M}$  through eigen-analysis to ensure the property of positive semi-definite. This simple algorithm has shown to perform surprisingly well on the person re-id problem [36, 19].

**kLFDA revisit.** kLFDA is a non-linear extension to LFDA [33] and has demonstrated the state-of-the-art performance on person re-id problem. kLFDA is a supervised dimensionality reduction method that uses a kernel trick to handle high dimensional feature vectors while maximizing the Fisher optimization criteria. A projection matrix  $\mathbf{M}$  can be achieved to maximize the between-class scatter matrix while minimizing the within-class scatter matrix for similar samples using the Fisher discriminant objective. kLFDA represents the projection matrix with data samples in the kernel space  $\phi(\cdot)$ . Once the kernel function is computed,  $\kappa(\mathbf{x}, \mathbf{x}') = \phi(\mathbf{x})^\top \phi(\mathbf{x}')$ , we can efficiently learn  $\mathbf{M}$ .

#### 4.5. Approximate kernel learning for person re-id

By projecting data points into high-dimensional or even infinite-dimensional feature space, kernel methods are found very effective in person re-id application with strong generalization performance [44]. However, one limitation of kernel methods is their high computational cost, which is at least quadratic in the size of training samples, due to the calculation of kernel matrix. In the testing stage, the kernel similarity between any two identities cannot be computed directly but through their individual kernel similarities to training individuals. Thus, the time complexity of testing heavily depends on the number of training samples. For instance, in CUHK03 data set, the number of individuals in the training is 1260, which would cause inefficiency in testing. To avoid computing kernel matrix, a kernel learning problem is often approximated by a linear prediction problem where the kernel similarity between any two data points is approximated by their vector representations. Whilst both random Fourier features [35] and the Nyström method [6] have been successfully applied to efficient kernel learning, recent theoretical and empirical studies show that the Nyström method has a significantly better generalization performance than random Fourier features when there is a large eigengap of kernel matrix [45].

The Nyström method approximates the kernel matrix by randomly selecting a subset of training examples and computes a kernel matrix  $\tilde{K}$  for the random samples, leading to data dependent vector representations. The additional error caused by the Nyström method in the generalization performance can be improved to be  $O(1/m)$  ( $m$  is the number of sampled training examples) when there is a large gap in the eigen-spectrum of the kernel matrix [45]. Thus, we employ an improved Nyström framework to approximate the kernel learning in large-sized person re-id databases. Specifically, given a collection of  $N$  training examples,  $X = \{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)\}$  where  $\mathbf{x}_i \in \mathcal{X} \subseteq \mathbb{R}^d$ ,  $y_i \in \mathcal{Y}$ . Let  $\kappa(\cdot, \cdot)$  be a kernel function,  $\mathcal{H}_k$  denote the endowed Reproducing Kernel Hilbert Space, and  $K = [\kappa(\mathbf{x}_i, \mathbf{x}_j)]_{N \times N}$  be the kernel matrix for the samples in  $X$ . The Nyström method approximates the full kernel matrix  $K$  by firstly sampling  $m$  examples, denoted by  $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_m$ , and then constructing a low rank matrix by  $\tilde{K}_r$  where  $r$  denotes the rank of  $\tilde{K} = [\kappa(\hat{\mathbf{x}}_i, \hat{\mathbf{x}}_j)]_{m \times m}$ . Thus, we can derive a vector representation of data by  $\mathbf{z}_n(\mathbf{x}) = \tilde{D}_r^{-1/2} \tilde{V}_r^T (\kappa(\mathbf{x}, \hat{\mathbf{x}}_1), \dots, \kappa(\mathbf{x}, \hat{\mathbf{x}}_m))^T$ , where  $\tilde{D}_r = \text{diag}(\hat{\lambda}_1, \dots, \hat{\lambda}_r)$ ,  $\tilde{V}_r = (\hat{\mathbf{v}}_1, \dots, \hat{\mathbf{v}}_r)$ ,  $\hat{\lambda}_i$  and  $\hat{\mathbf{v}}_i$  denote the eigenvalue and eigenvector of  $\tilde{K}_r$ , respectively. Given  $\mathbf{z}_n(\mathbf{x})$ , we aim to learn a linear



**Figure 2:** HS and RGB histograms extracted from overlapping stripes.

machine  $f(\mathbf{x}) = \mathbf{w}^T \mathbf{z}_n(\mathbf{x})$  by solving the following optimization problem:

$$\min_{\mathbf{w} \in \mathbb{R}^r} \frac{\lambda}{2} \|\mathbf{w}\|_2^2 + \frac{1}{N} \sum_{i=1}^N l(\mathbf{w}^T \mathbf{z}_n(\mathbf{x}_i), y_i). \quad (10)$$

In [45], Yang *et al.* construct an approximate functional space  $\mathcal{H}_a = \text{span}(\hat{\phi}_1, \dots, \hat{\phi}_r)$  where  $\hat{\phi}_1, \dots, \hat{\phi}_r$  are the first  $r$  normalized eigenfunctions of the operator  $L_m = \frac{1}{m} \sum_{i=1}^m \kappa(\hat{\mathbf{x}}_i, \cdot) f(\hat{\mathbf{x}}_i)$  and they subsequently obtain the following equivalent approximate kernel machine:

$$\min_{f \in \mathcal{H}_a} \frac{\lambda}{2} \|f\|_{\mathcal{H}_k}^2 + \frac{1}{N} \sum_{i=1}^N l(f(\mathbf{x}_i), y_i).$$

According to both theoretical and empirical studies, the additional error caused by this approximation of the Nyström method is improved from  $O(1/\sqrt{m})$  to  $O(1/m)$  when there is a large gap between  $\lambda_r$  and  $\lambda_{r+1}$ . In our experimental study (section 5.8), the eigenvalue distributions of kernel matrices from different person re-id data sets are shown to demonstrate the existence of large eigengap in kernel matrices.

## 5. Experiments

### 5.1. Visual feature implementations

In this section, we introduce five low-level visual features which describe different aspects of person images, and can be well crafted to show promising results in person re-identification. To particularly cater for person re-id data sets, these feature descriptors are well manipulated in their implementations with configurations and settings best tuned.

**LAB patterns.** For color patterns, we extract color features using 32-bins histograms at three different scale factors (0.5, 0.75 and 1) over three different channels: L, A and B. Finally, each histogram feature is normalized with the  $\ell_2$ -norm and concatenated to form the final feature descriptor vector with length 4032.

*LBP patterns.* Local Binary Pattern (LBP) is an effective feature descriptor in describing local image texture and their occurrence histogram [30]. The standard 8-neighbours LBP has a radius of 1 and is formed by thresholding the  $3 \times 3$  neighbourhood centred at a pixel's value. To improve the classification accuracy of LBP, we combine LBP histograms with color histograms extracted from the RGB colorspace. The LBP/RGB implementation is obtained from [44]. Specifically, on each pedestrian image with resolution  $48 \times 128$  pixels, LBP and color histograms are extracted over a set of 7 dense overlapping  $48 \times 32$ -pixels regions with a stepping stride of 16 pixels in the vertical direction. For texture pattern, we extract LBP histograms using 8-neighbours (radius 1 and 2) and 16-neighbours (radius 2 and 3). LBP is applied to grayscale image and each RGB color channel. We adopt an extension of LBP, known as the uniform LBP, which can better filter out noises [40]. For color histogram, we extract color features using 16-bins histograms over six color channels: R, G, B, Y, Cb and Cr. Finally, each histogram feature is normalized with the  $\ell_1$ -norm and concatenated to form a feature vector of 9352 dimensions.

*Hue-Saturation (HS) histogram.* We first re-scale an image to a broader size  $64 \times 128$ , and then build a spatial pyramid by dividing the image into overlapping horizontal stripes of 16 pixels in height. The HS histograms contain  $8 \times 8$  bins, which are computed for the 15 levels of the pyramids (i.e., 8 stripes for the first level plus 7 for the second level of overlapping stripes, where the second level of stripes are created from a sub-image by removing 8 pixels from top, bottom, left, and right of the original in order to remove background interference.). Each feature histogram is normalized with the  $\ell_2$ -norm and we have the vector length to be 960.

*RGB histogram.* RGB is quantized into  $8 \times 8 \times 8$  over R, G, B channels. Like the extraction of HS, RGB histograms are also computed for the 15 levels of the pyramids, and each histogram feature is normalized with the  $\ell_2$ -norm, forming 7680-dim feature descriptor. We illustrate the procedure of extracting HS and RGB histograms in Fig. 2. Horizontal stripes capture information about vertical color distribution in the image, while overlapping stripes maintain color correlation between adjacent stripes in the final descriptor [22]. Overall, HS histogram renders a portion of the descriptor invariant to illumination variations, while the RGB histograms capture more discriminative color information, especially for dark and greyish colors.

*SIFT features.* Scale-invariant feature transform (SIFT) is widely used for recognition task due to its invariance to scaling, orientation and illumination changes [25]. The descriptor represents occurrences of gradient orientation in each region. In this work, we employ discriminative SIFT extracted from the LAB color space. On a person image with a resolution of  $48 \times 128$  pixels, SIFT are extracted over a set of 14 dense overlapping  $32 \times 32$ -pixels regions with a stepping stride of 16 pixels in both directions. Specifically, we divide each region into  $4 \times 4$  cells and set the number of orientation bins to 8. As a result, we can obtain the feature vector with length 5376. In this paper, we use the SIFT/LAB implementation obtained from [47].

## 5.2. Experimental settings

*Datasets.* In this experiment, six publicly available person re-identification data sets, iLIDS, 3DPES, PRID2011, VIPeR, CUHK01 and CUHK03 are used for evaluation. The iLIDS data set has 119 individuals captured from eight cameras with different viewpoints [50]. The 3DPeS data set contains numerous video sequences taken from a real surveillance environment with eight different surveillance cameras and consists of 192 individuals [1]. The Person RE-ID 2011 (PRID2011) data set consists of images extracted from multiple person trajectories recorded from two surveillance static cameras [13]. Camera view A contains 385 individuals, camera view B contains 749 individuals, with 200 of them appearing in both views. Hence, there are 200 person image pairs in the dataset. VIPeR [10] contains 632 individuals taken from two cameras with arbitrary viewpoints and varying illumination conditions. The CUHK01 data set contains 971 persons captured from two camera views in a campus environment [18] where one camera captures the frontal or back view of the individuals while another camera captures the profile view. Finally, the CUHK03 data set consists of 1467 persons taken from six cameras [19]. The data set consists of manually cropped pedestrian images and images cropped from the pedestrian detector of [8]. In our experiment, we use images which are manually annotated.

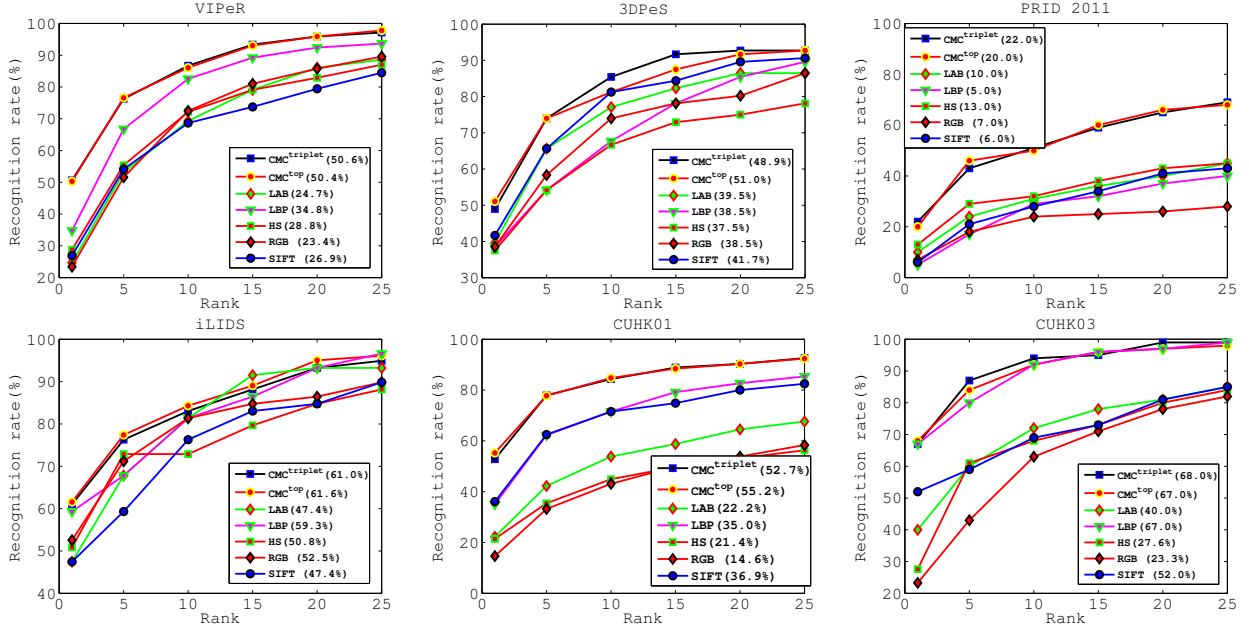
*Evaluation protocol.* In this paper, we adopt a single-shot experiment setting, similar to [20, 33, 44, 48, 51]. For all data sets except CUHK03, all individuals in the data set are randomly divided into two subsets so that training set and test set contains half of the individuals with no overlap on person identities. For data set with two cameras, we randomly select two images of the same individual taken from two cameras as the probe image and the gallery image<sup>2</sup>, respectively. For multi-camera data sets, two images of the same individual are chosen: one is used as the probe image and the other as the gallery image. For CUHK03, we set the number of individuals in the train/test split to 1366/100 as conducted in [19]. The split on training and test set on different data sets are shown in Table 2. This procedure is repeated 10 times and the average of cumulative matching characteristic (CMC) curves across 10 partitions is reported.

*Competitors.* We consider the following state-of-the-art as competitors: 1) MidLevel [48]; 2) LADF [20]; 3) SalMatch [46]; 4) KISSME [17]; 5) PCCA [27]; 6) PRDC [49]; 7) eSDC [47]; 8) SDALF [7]; 9) ISR [22]; 10) ITML [5]; 11) LMNN [41]. Each algorithm is tuned to show their best performance.

*Parameters setting.* For the linear base metric (KISS ML [17]), we apply principal component analysis (PCA) to reduce the dimensionality and remove noise. For each visual feature, we reduce the feature dimension to 64 dimensional subspaces. For

<sup>2</sup>In a multi-camera setup, the probe and gallery samples are defined as two samples which are randomly chosen from all the available cameras, one serving as the probe and the other as the gallery.





**Figure 3:** Performance comparison of base metrics (non-linear) with different visual features: LAB, LBP, HS, RGB histogram, and SIFT. Rank-1 recognition rates are shown in parentheses. The higher the recognition rate, the better the performance. CMC<sup>top</sup> represents our ensemble approach which optimizes the CMC score over the top  $k$  returned candidates. CMC<sup>triplet</sup> represents our ensemble approach which minimizes the number of returned candidates such that the rank- $k$  recognition rate is equal to one.

the non-linear base metric (kLFDA [44]), we set the regularization parameter for class scatter matrix to 0.01, i.e., we add a small identity matrix to the class scatter matrix. For all features, we apply the RBF- $\chi^2$  kernel. The kernel parameter is tuned to an appropriate value for each data set. In this experiment, we set the value of  $\sigma^2$  to be the same as the first quantile of all distances [44]. For CMC<sup>triplet</sup>, we choose the regularization parameter ( $\nu$  in (1)) from  $\{10^3, 10^{3.1}, \dots, 10^4\}$  by cross-validation on the training data. For CMC<sup>top</sup>, we choose the regularization parameter ( $\nu$  in (6)) from  $\{10^2, 10^{2.1}, \dots, 10^3\}$  by cross-validation on the training data. We set the cutting-plane termination threshold to  $10^{-6}$ . The recall parameter ( $k$  in (5)) is set to be 10 for iLIDS, 3DPeS, PRID2011 and VIPeR and 30 for larger data sets (CUHK01 and CUHK03).

### 5.3. Evaluation and analysis

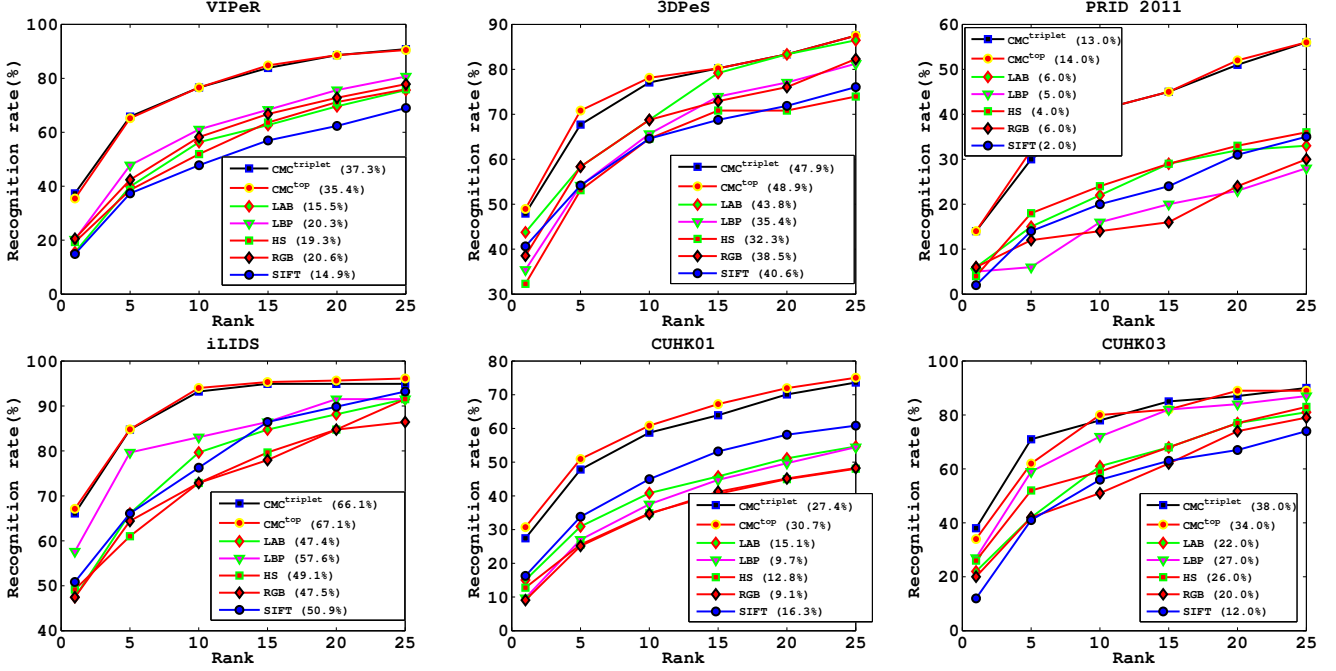
Since distance functions of different features have different scales, we normalize the distance between each probe image to all images in the gallery to be between zero and one. In other words, in all experiments, we set the distance between the probe image and the nearest gallery image to be zero and the distance between the probe image and the furthest gallery image to be one.

*Feature evaluation.* We investigate the impact of low-level visual features on the recognition performance of person re-id. Fig. 3 shows the CMC performance of different visual features and their rank-1 recognition rates when trained with the kernel-based LFDA on six benchmark data sets. We have the following observations:

- In VIPeR, iLIDS, and CUHK03 data sets, LBP and LAB are more effective than other features. Since LBP encodes texture and color features, we suspect the use of color helps improve the overall recognition accuracy of LBP. In these data sets, a large number of persons wear similar types of clothing but with different color. Therefore, color information becomes an important cue for recognizing two different individuals. In some scenarios where color cue is not reliable because of illuminations, texture helps to identify the same individual.
- In 3DPeS and CUHK01 data sets, SIFT and LBP are more effective in recognition. This can be ascribed to the fact that many samples are captured by zoomed/translated cameras (in 3DPeS) or orientation changes (in CUHK01) whilst SIFT is invariant to scale and orientation.
- In PRID 2011 database, HS becomes predominant feature. This is because this database consist of images captured with little exposure to illuminations in which both color and texture cues become unreliable whilst HS histograms are invariant to illumination changes.

In fact, these person re-id data sets are created with distinct photometric and geometric transformations due to their own lighting conditions and camear settings. In this end, low-level features that are combined properly can be used to characterize the designed features of these data sets. Since our proposed optimization yields a weight vector for distance functions, it is informative to characterize the nature of different test data sets and the effects of low-level features in recognizing persons are adaptive to these data sets. We show the weight distributions of





**Figure 4:** Performance comparison of base metrics (linear) with different visual features: LAB, LBP, HS, RGB histogram, and SIFT. Rank-1 recognition rates are shown in parentheses. The higher the recognition rate, the better the performance. CMC<sup>top</sup> represents our ensemble approach which optimizes the CMC score over the top  $k$  returned candidates. CMC<sup>triplet</sup> represents our ensemble approach which minimizes the number of returned candidates such that the rank- $k$  recognition rate is equal to one.

corresponding features on six benchmarks in Fig. 5. It can be seen that

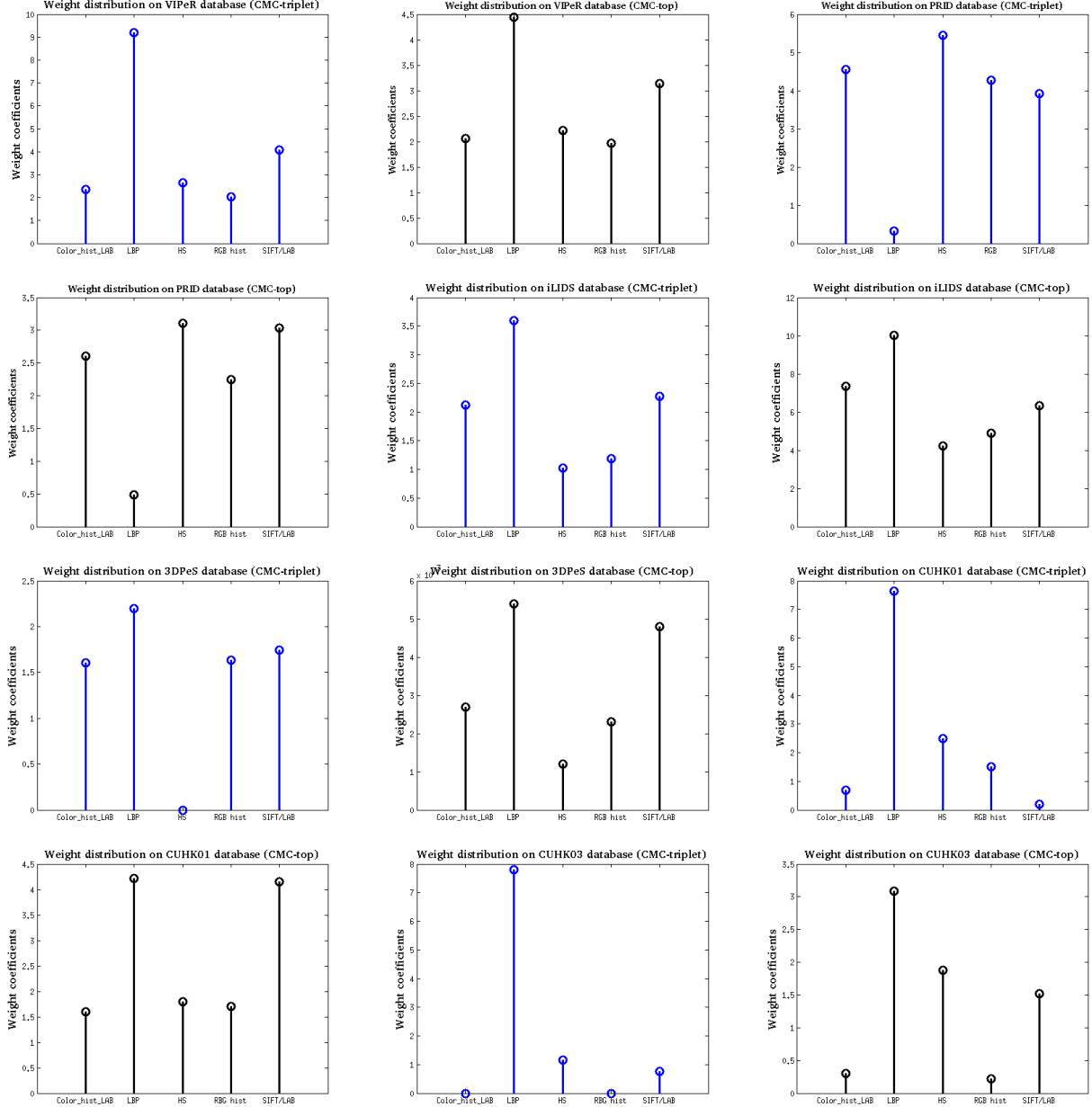
- in VIPeR, iLIDS and 3DPeS data sets, the features of color, LBP and SIFT are more effective, thus they are more likely to be assigned larger weight coefficients.
- In CUHK01 and CUHK03 databases, LBP, SIFT and HS are more helpful to recognize individuals due to the fact that many samples in the two data sets undergo photometric and geometric transforms caused by the change of lighting conditions, viewpoints, and human-pose whereas SIFT and HS are invariant to orientation and illumination changes, respectively.
- In PRID 2011 data set, HS and color information (LAB and RGB) are predominant features.

We also provide experimental results of *linear metric learning* [17] with different visual features. The CMC curve can be found in Fig. 4. Recall Fig. 3, we observe that: 1) non-linear based kernels perform better than linear metrics on most visual features. A significant performance improvement is found in CUHK03 data set, where we observe a performance improvement from 12.0% to 52.0% for SIFT features, and an improvement from 27.0% to 67.0% for LBP features; 2) our method is highly flexible to both linear/non-linear metric learning, and the effects of visual features in recognizing persons are almost the same in using linear or non-linear metric learning.

*Ensemble approach with linear/non-linear metric learning.* We conduct the performance comparison of our approach with two

different base metrics: linear metric learning (KISSME) [17] and kernel metric learning (kLFDA) [44]. In this experiment, we use CMC<sup>top</sup> to learn an ensemble. Experimental results are shown in Fig. 6. Some observations can be seen from the figure: 1) both approaches perform similarly when the number of train/test individuals is small, e.g., on iLIDS and 3DPeS; 2) non-linear base metric outperforms linear base metric by a large margin when the number of individuals increase as in CUHK01 and CUHK03 data sets. This is because KISSME employs PCA to reduce the dimensionality of data since it requires solving a generalized eigenvalue problem of very large scatter  $d \times d$  matrices where  $d$  denotes the dimensionality of features. However, this dimensionality step, when applied to relatively diverse data set, can result in an undesirable compression of the most discriminative features. In contrast, kLFDA can avoid performing such decomposition, and flexible in choosing the kernel to improve the classification accuracy; 3) the combination of the two types of metrics cannot help improving the recognition rate.

*Performance at different recall values.* Next we compare the performance of CMC<sup>triplet</sup> with CMC<sup>top</sup>. Both algorithms optimize the recognition rate of person re-id but with different objective criteria. kLFDA is employed as the base metric. The matching accuracy is shown in Table 1. We observe that CMC<sup>top</sup> achieves the best recognition rate performance at a small recall value. At a large recall value (rank  $\geq 50$ ), both CMC<sup>top</sup> and CMC<sup>triplet</sup> perform similarly. We also evaluate to see how CMC<sup>top</sup> varies against different values of  $k$  (optimize the rank- $k$  recognition rate). Results are shown in Table 3.



**Figure 5:** Weight distributions on six datasets that can reflect the adaptive effects of low-level features in recognizing individuals. The higher the coefficient is, the more important the feature is. It shows that the effectiveness of these features varied upon different datasets, which can be quantified in their weight values.

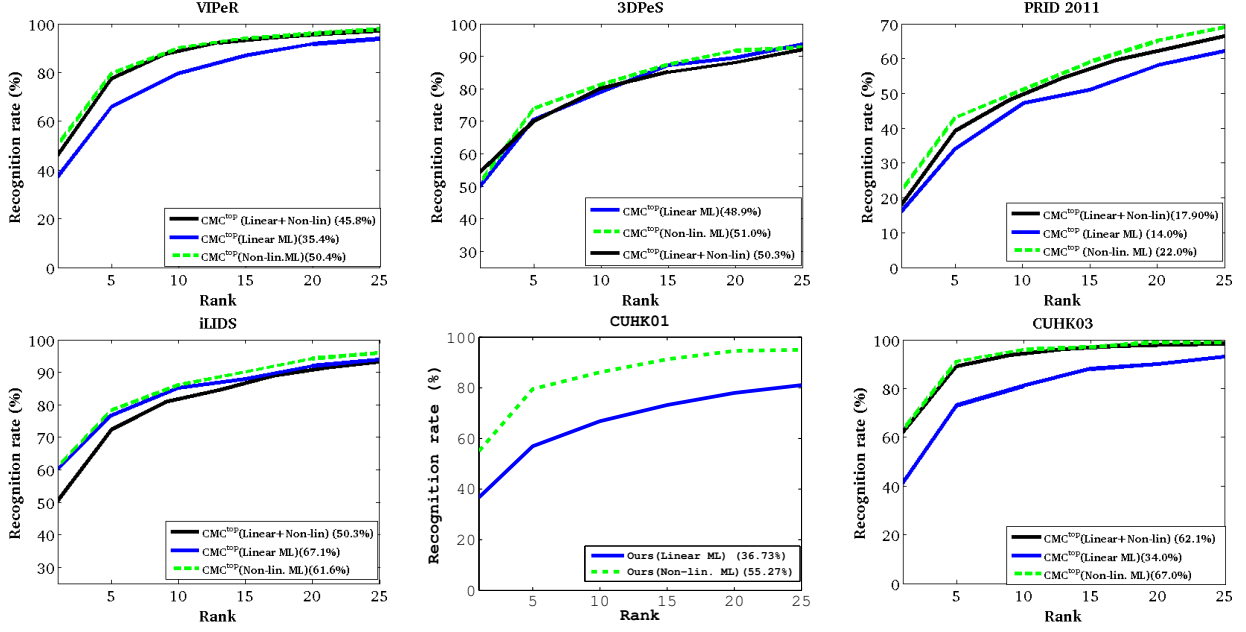
#### 5.4. Comparison with state-of-the-art results

Fig. 7 compares  $\text{CMC}^{\text{top}}$  (kLFDA is used as the base metric) with other person re-id algorithms on two major benchmark data sets: VIPeR and CUHK01. Our approach outperforms all existing person re-id algorithms. Then we compare  $\text{CMC}^{\text{top}}$  with the best reported results in the literature, as shown in Table 2. The algorithm proposed in [44] achieves state-of-the-art results on iLIDS and 3DPeS data sets (40.3% and 54.2% recognition rate at rank-1, respectively).  $\text{CMC}^{\text{top}}$  outperforms [44] on the iLIDS (61.3%) by a large margin, and achieves a comparable result on 3DPeS (51.1%). Zhao *et al.* propose mid-level filters for person re-identification [48], which achieve state-of-

the-art results on the VIPeR and CUHK01 data sets (43.39% and 34.30% recognition rate at rank-1, respectively).  $\text{CMC}^{\text{top}}$  outperforms [48] by achieving a recognition rate of 50.6% and 55.2% on the VIPeR and CUHK01 data sets, respectively.

#### 5.5. Comparison with a structured learning-based person re-id

In this section, we compare our ensemble approaches with another structured learning-based method for person re-identification [43]. In [43] a metric learning to rank (MLR) algorithm [26] is applied to the person re-identification problem with a listwise loss function and evaluated on Mean Reciprocal Rank (MRR). For a fair comparison, we concatenate low-



**Figure 6:** Performance comparison of  $\text{CMC}^{\text{top}}$  with two different base metrics: linear metric learning (KISSME) [17] non-linear metric learning [44] (kLFDA with  $\text{RBF-}\chi^2$  kernel), and their combination. On VIPeR, PRID 2011, CUHK01 and CUHK03 data sets, an ensemble of non-linear base metrics significantly outperforms an ensemble of linear base metrics.

**Table 1:** Re-id recognition rate (%) at different recall (rank). The best result is shown in boldface. Both  $\text{CMC}^{\text{top}}$  and  $\text{CMC}^{\text{triplet}}$  achieve similar performance when retrieving  $\geq 50$  candidates.

Rank	VIPeR			CUHK01			CUHK03		
	Avg.	$\text{CMC}^{\text{triplet}}$	$\text{CMC}^{\text{top}}$	Avg.	$\text{CMC}^{\text{triplet}}$	$\text{CMC}^{\text{top}}$	Avg.	$\text{CMC}^{\text{triplet}}$	$\text{CMC}^{\text{top}}$
1	50.4	50.3	<b>50.6</b>	52.5	53.0	<b>55.2</b>	59.5	67.0	<b>68.1</b>
2	61.0	61.4	<b>61.4</b>	63.5	64.1	<b>64.9</b>	71.9	74.0	<b>77.8</b>
5	76.5	77.3	<b>77.6</b>	77.1	76.7	<b>77.5</b>	86.4	85.8	<b>89.3</b>
10	88.4	88.6	<b>88.9</b>	84.3	<b>84.8</b>	84.5	92.3	92.5	<b>95.3</b>
20	95.9	95.9	<b>95.9</b>	92.1	91.7	<b>92.5</b>	96.9	<b>99.0</b>	97.0
50	99.4	<b>99.7</b>	99.5	97.0	<b>97.1</b>	96.9	99.8	99.7	<b>100.0</b>
100	99.9	100.0	<b>100.0</b>	98.6	98.6	<b>98.6</b>	100.0	100.0	<b>100.0</b>

**Table 2:** Rank-1 recognition rate of existing best reported results and  $\text{CMC}^{\text{top}}$  results.

Data set	# Individuals		Prev. best	$\text{CMC}^{\text{top}}$
	train	test		
iLIDS	59	60	40.3% [44]	<b>61.6%</b>
3DPeS	96	96	<b>54.2%</b> [44]	51.1%
PRID2011	100	100	16.0% [36]	<b>22.0%</b>
VIPeR	316	316	43.4% [48]	<b>50.6%</b>
CUHK01	486	485	34.3% [48]	<b>55.2%</b>
CUHK03	1366	100	20.7% [19]	<b>68.0%</b>

level visual features and learn MLR [43] and LMNN [41] on VIPeR data set. We choose the MLR trade-off parameter from  $\{10^{-5}, 10^{-4}, \dots, 10^5\}$ . The rank-1 recognition rate and mean reciprocal rank (MRR) are shown in the Table 4. We can see that our ensemble approach significantly outperforms both baseline

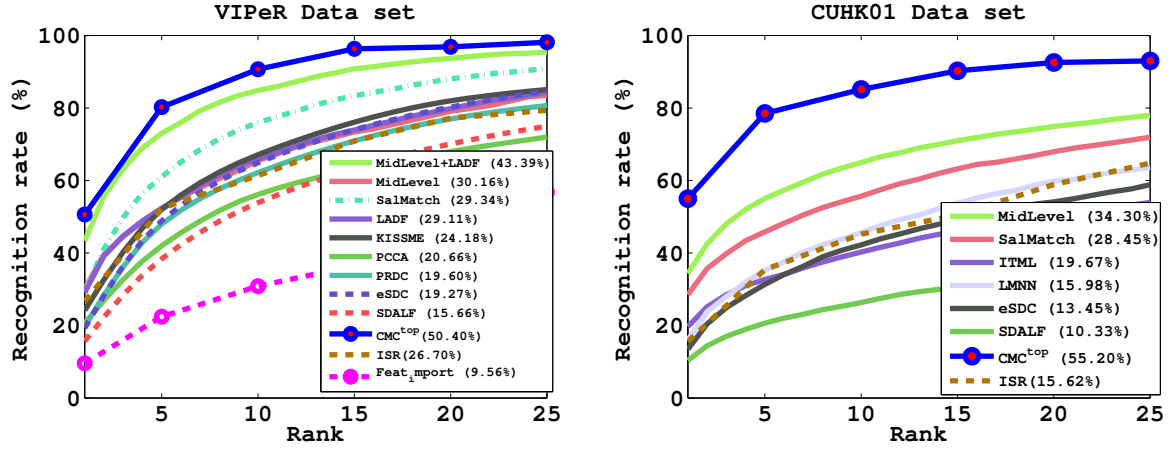
**Table 3:** Rank-1 recognition rate of  $\text{CMC}^{\text{top}}$  with varied value of  $k$ .

$k$	VIPeR	PRID 2011	3DPeS	iLIDS	CUHK01	CUHK03
10	50.4%	20.0%	51.0%	61.6%	-	-
20	50.4%	20.0%	51.2%	61.3%	-	-
30	49.8%	19.4%	50.7%	61.0%	55.2%	67.1%
40	48.4%	18.4%	50.1%	60.3%	55.2%	67.0%
50	48.1%	18.2%	48.4%	58.1%	55.0%	66.8%

methods under both evaluation criteria.

### 5.6. Compatibility to early fusion of features

Concatenating low-level features has been demonstrated to be powerful in person re-id application [48, 47]. Our approaches can be essentially regarded as a late fusion paradigm where base metrics are first learnt from training samples, which are then fed into visual features to seek their individual weights. In this section, we study the compatible property of our method



**Figure 7:** CMC performance for VIPeR and CUHK01 data sets.  $\text{CMC}^{\text{top}}$  outperforms all existing person re-id algorithms.

to early fusion of visual features. Since we have five types of hand-crafted features, hence there are  $\sum_{k=1}^5 C_5^k$  combinatorial strategies in total, as shown in Table 5, where  $\checkmark$  denotes the selection of candidate features in concatenation. For instance,  $F_6$  indicates a feature which is formed by concatenating  $F_1$  (LAB) and  $F_2$  (LBP) into a single feature vector. Our approaches are conducted to learn weights for ensembling these base metrics. Evaluation results are reported in Table 6–8, where kLFDA is employed to perform metric learning. We have the following observations:

- Our ensemble-based approaches consistently outperform any kind of concatenated features in rank- $k$  recognition rates, demonstrating the effectiveness in combining these features with adaptive weights. Simply concatenating features is essentially to assign equally pre-defined weights to their metric, which is not robust enough against complex variations in illumination, pose, viewpoints, camera setting, and background clutter across camera views.
- Incorporating more base metrics is beneficial to our algorithms. In most cases, the increasingly availability of base metrics contribute to either achieve slight improvement in rank- $k$  recognition rate or keep the state-of-the-art results from Table 2. This demonstrates the robustness of our approaches against feature selection.
- Some low-level features are complementary to each other, and consequently, their concatenations give promising re-

sults, e.g., in iLIDS, F22 (concatenation of LBP, HS, and RGB histogram) shows superior performance to other fusion strategies. However, this pre-defined combination is lack of generalization, and only suits to specific data sets, e.g., in 3DPeS, F22 is inferior to F25.

**Table 5:** The indication table for early fusion strategies of low-level features. LAB (F1), LBP (F2), HS (F3), RGB (F4), SIFT(F5).

	F1	F2	F3	F4	F5		F1	F2	F3	F4	F5
F6	$\checkmark$	$\checkmark$				F19	$\checkmark$		$\checkmark$		
F7	$\checkmark$		$\checkmark$			F20	$\checkmark$		$\checkmark$	$\checkmark$	$\checkmark$
F8	$\checkmark$			$\checkmark$		F21	$\checkmark$		$\checkmark$	$\checkmark$	
F9	$\checkmark$				$\checkmark$	F22		$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
F10		$\checkmark$	$\checkmark$			F23		$\checkmark$	$\checkmark$	$\checkmark$	
F11		$\checkmark$		$\checkmark$		F24		$\checkmark$		$\checkmark$	$\checkmark$
F12			$\checkmark$		$\checkmark$	F25			$\checkmark$	$\checkmark$	$\checkmark$
F13			$\checkmark$	$\checkmark$		F26	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
F14			$\checkmark$		$\checkmark$	F27	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
F15				$\checkmark$	$\checkmark$	F28	$\checkmark$		$\checkmark$	$\checkmark$	$\checkmark$
F16	$\checkmark$	$\checkmark$	$\checkmark$			F29	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
F17	$\checkmark$	$\checkmark$		$\checkmark$		F30		$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
F18	$\checkmark$	$\checkmark$			$\checkmark$	F31	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$

### 5.7. Comparison with metric learning algorithms

We evaluate the performance on different metric learning algorithms: large scale metric learning from equivalence constraints (KISSME) [17]<sup>3</sup>, large margin nearest neighbor (LMNN)

<sup>3</sup><http://lrs.icg.tugraz.at/research/kissme/>

**Table 4:** Rank-1 recognition rate and mean reciprocal rank (MRR) of different algorithms. The experimental result reported here for MLR+MRR is better than the one reported in [43] as the authors only use color histogram feature.

Algorithm	Rank-1 rate	MRR
LMNN [41]	24.9%	37.8%
MLR+MRR [43]	26.2%	39.9%
$\text{CMC}^{\text{top}}$ + linear metric	37.3%	47.3%
$\text{CMC}^{\text{top}}$ + non-linear metric	50.6%	60.1%

**Table 6:** Rank-1, Rank-5, and Rank-10 recognition rate of various early fusion strategies over VIPeR and iLIDS databases.

Feature	VIPeR			iLIDS		
	CMC(1)	CMC(5)	CMC(10)	CMC(1)	CMC(5)	CMC(10)
F1	22.4%	50.6%	67.7%	47.4%	67.7%	81.3%
F2	35.4%	63.6%	77.2%	59.3%	67.7%	81.3%
F3	23.7%	54.4%	70.2%	50.8%	72.8%	72.8%
F4	26.2%	53.4%	69.3%	52.5%	71.1%	81.3%
F5	27.8%	54.7%	68.6%	47.4%	59.3%	76.2%
F6	31.0%	63.2%	78.1%	49.1%	71.1%	83.0%
F7	29.1%	61.0%	76.8%	50.8%	69.4%	79.6%
F8	25.6%	60.7%	76.5%	54.2%	69.4%	79.6%
F9	34.4%	68.6%	80.0%	54.2%	71.1%	74.5%
F10	39.5%	69.6%	82.9%	60.7%	77.9%	84.7%
F11	38.6%	70.2%	84.8%	59.3%	72.8%	86.4%
F12	35.7%	68.9%	82.5%	55.9%	66.1%	77.9%
F13	34.1%	68.3%	82.2%	52.5%	71.1%	74.5%
F14	38.9%	68.6%	81.3%	50.8%	69.4%	79.6%
F15	37.6%	71.2%	83.5%	50.8%	62.7%	79.6%
F16	34.8%	68.9%	81.9%	54.2%	72.8%	84.7%
F17	31.6%	70.2%	82.2%	54.2%	71.1%	83.0%
F18	38.9%	72.1%	84.4%	55.9%	71.1%	79.6%
F19	31.9%	66.4%	81.6%	57.6%	71.2%	83.0%
F20	37.3%	73.1%	81.6%	57.6%	71.1%	76.2%
F21	35.7%	71.2%	82.9%	55.9%	71.1%	76.2%
F22	40.1%	75.3%	86.0%	60.7%	74.5%	83.0%
F23	40.8%	74.0%	84.4%	59.3%	67.7%	83.0%
F24	43.3%	75.3%	85.4%	54.2%	66.1%	79.6%
F25	41.4%	74.3%	84.8%	54.2%	72.8%	76.2%
F26	34.1%	72.1%	84.4%	57.6%	71.2%	84.7%
F27	40.1%	75.6%	86.0%	57.6%	72.8%	79.6%
F28	39.2%	73.4%	86.0%	54.2%	72.8%	77.9%
F29	38.9%	74.0%	84.8%	55.9%	71.1%	76.2%
F30	45.8%	75.9%	88.2%	55.9%	69.4%	83.0%
F31	41.7%	75.6%	87.0%	57.6%	72.8%	79.6%
CMC <sup>top</sup>	<b>47.1%</b>	<b>79.7%</b>	<b>88.6%</b>	<b>61.0%</b>	<b>76.3%</b>	<b>86.4%</b>
CMC <sup>triplet</sup>	<b>47.7%</b>	<b>79.1%</b>	<b>88.9%</b>	<b>61.3%</b>	<b>77.1%</b>	<b>86.7%</b>

**Table 7:** Rank-1, Rank-5, and Rank-10 recognition rate of various early fusion strategies over PRID2011 and 3DPeS databases.

Feature	PRID 2011			3DPeS		
	CMC(1)	CMC(5)	CMC(10)	CMC(1)	CMC(5)	CMC(10)
F1	10.1%	24.0%	31.0%	39.5%	65.6%	77.1%
F2	5.0%	17.0%	29.0%	38.5%	54.1%	67.7%
F3	13.0%	29.0%	32.0%	37.5%	54.1%	66.7%
F4	7.0%	18.0%	24.0%	38.5%	58.3%	73.9%
F5	6.0%	21.0%	28.0%	41.6%	65.6%	81.2%
F6	10.0%	28.0%	36.0%	40.6%	68.7%	76.0%
F7	11.0%	28.0%	35.0%	43.7%	67.7%	78.1%
F8	11.0%	28.0%	33.0%	39.5%	65.6%	79.1%
F9	9.0%	29.0%	38.0%	48.9%	71.8%	81.2%
F10	11.1%	24.0%	34.0%	40.6%	59.3%	72.9%
F11	8.0%	17.0%	30.0%	38.5%	56.2%	73.9%
F12	7.0%	22.0%	35.0%	42.7%	70.8%	84.3%
F13	15.0%	33.0%	36.0%	38.5%	64.5%	72.9%
F14	7.0%	21.0%	33.0%	48.9%	73.9%	80.2%
F15	10.0%	23.0%	32.0%	48.9%	76.0%	84.4%
F16	14.0%	28.0%	35.0%	44.7%	68.7%	78.1%
F17	9.0%	29.0%	36.0%	43.7%	67.7%	75.0%
F18	11.0%	31.0%	35.0%	44.7%	71.8%	82.2%
F19	14.0%	33.0%	39.0%	40.6%	64.5%	76.0%
F20	9.0%	32.0%	41.0%	47.9%	70.8%	79.1%
F21	9.0%	28.0%	39.0%	47.9%	72.9%	81.2%
F22	13.0%	26.0%	37.0%	39.5%	60.4%	77.0%
F23	11.0%	24.0%	34.0%	46.8%	77.0%	81.2%
F24	11.0%	25.0%	37.0%	45.8%	75.0%	82.2%
F25	8.0%	21.0%	32.0%	51.0%	73.9%	80.2%
F26	13.0%	30.0%	37.0%	43.7%	68.7%	77.0%
F27	14.0%	30.0%	39.0%	46.8%	70.8%	81.2%
F28	10.0%	31.0%	36.0%	46.8%	75.0%	82.2%
F29	14.0%	32.0%	40.0%	48.9%	70.8%	80.2%
F30	14.0%	27.0%	33.0%	46.8%	72.9%	81.2%
F31	14.0%	28.0%	37.0%	46.8%	69.7%	82.2%
CMC <sup>top</sup>	<b>21.0%</b>	<b>41.0%</b>	<b>49.0%</b>	<b>50.0%</b>	<b>79.1%</b>	<b>85.4%</b>
CMC <sup>triplet</sup>	<b>20.0%</b>	<b>42.0%</b>	<b>50.0%</b>	<b>47.9%</b>	<b>72.9%</b>	<b>83.2%</b>

[41]<sup>4</sup> and logistic distance metric learning (LDML) [12]<sup>5</sup>.

*Metric learning.* We first apply principal component analysis (PCA) to reduce the dimensionality and remove noise. Without performing PCA, it is computationally infeasible to perform metric learning on KISSME. To ensure a fair comparison, we use the same number of PCA dimensions in all metric learning algorithms. In this experiment, we reduce the feature dimension to 32, 64, and 100 dimensional subspaces. The setting of parameters for these metric learning algorithms are as follows: For KISSME and LDML, all parameters are set to be the default values as suggested by the authors [17, 12]. In the LMNN algorithm, we keep most parameters to be default values as suggested by the authors [41] while changing the number of nearest neighbors to be 1 and the maximum number of iterations to 1000 to speed up the experiment. (The default is 10000).

*Experimental results.* We compare rank-1 identification rates of three different metric learning algorithms in Table 9 (The results with 32-dim and 100-dim are shown in parentheses). The three metric learning algorithms first apply PCA to reduce the dimension of each feature and then take the concatenation as input. CMC<sup>top</sup> is conducted to learn a set of weights adaptive to these distance functions. We observe that we achieve

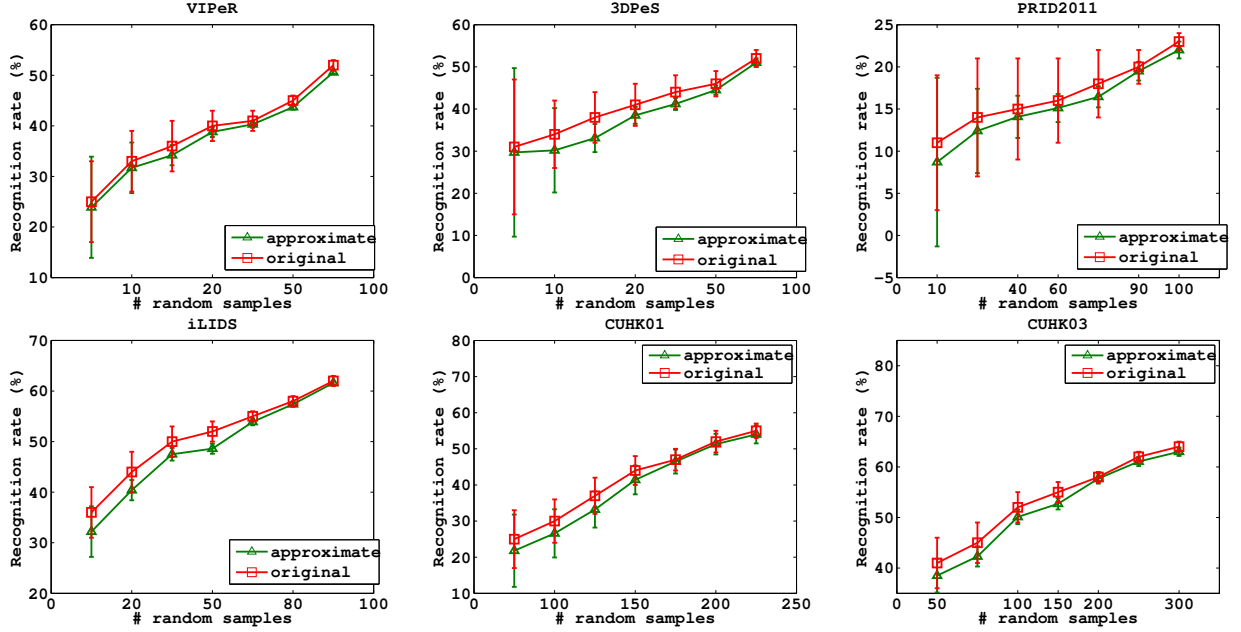
superior performance to state-of-the-art metric learning methods that combine the same range of feature vectors as input. However the performance of all metric learning algorithms improves as we increase the number of PCA dimensions. Possible reasons that might have caused significant performance differences between our obtained results and baselines of metric learning are: (a) learning weights for distance functions is more adaptive to sample variations in a variety of person re-id databases; (b) optimizing the test criteria directly is beneficial to improving recognition rate.

### 5.8. Approximating kernel learning

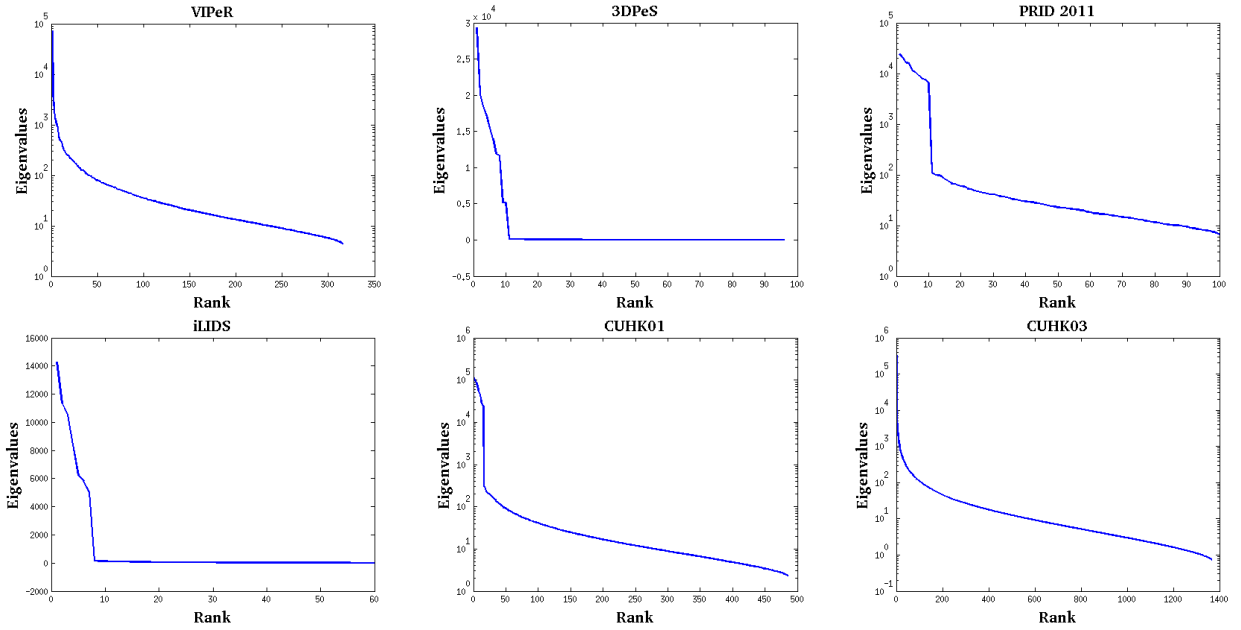
As shown in above empirical study, an ensemble of kernel based metrics remarkably outperforms that of liner base metrics, especially in VIPeR, PRID 2011, CUHK01 and CUHK03. Nonetheless, the application of non-linear metric learning is recognized to be limited in the case of large-scale data set such as CUHK03 or even medium-sized data set such as CUHK01 due to the high computational cost in kernel learning. To this end, we resort to approximate kernel learning by using the Nyström method which is able to approximate the full kernel matrix by a low rank matrix with the additional error of  $O(1/m)$  in the generalization performance. Fig. 8 shows the performance of our method with varied number of random samples. Note that for the large data set CUHK03, we restrict the maximum number of random samples to 300 because of the high computational cost. We observe that the approximate counter-

<sup>4</sup><http://www.cse.wustl.edu/~kilian/code/lmnn/lmnn.html>

<sup>5</sup><http://lear.inrialpes.fr/people/guillaumin/code.php>



**Figure 8:** Approximate kernel learning by using the Nyström method. The recognition rate at rank-1 of CMC<sup>top</sup> is reported (with std.) against varied number of random samples. The more samples we use, the more accurate results will be. To make the computation efficient, we select less than 300 samples to compute the kernel, which can approximate kernel learning without losing much recognition values compared with the original.



**Figure 9:** The eigenvalue distributions of kernel matrices. For each dataset, the eigenvalues drop very quickly as the rank increases, leading to a large gap between the top eigenvalue and the remainings. This justifies the feasibility of Nyström method on person re-id.

part is able to achieve comparable results to the original method with a full kernel matrix. We finally evaluate whether the key assumption of large eigengap holds for these person re-id data sets. As shown in Fig. 9 (eigenvalues are in logarithm scale), it can be seen that the eigenvalues drop very quickly as the rank increases, yielding a dramatic gap between the top eigenvalues

and the remaining ones.

## 6. Conclusion

In this paper, we have presented two effective structured learning based approaches for person re-id by combining mul-



**Table 8:** Rank-1, Rank-5, and Rank-10 recognition rate of various early fusion strategies over CUHK01 and CUHK03 databases.

Feature	CUHK01			CUHK03		
	CMC(1)	CMC(5)	CMC(10)	CMC(1)	CMC(5)	CMC(10)
F1	18.7%	40.0%	51.9%	30.0%	60.0%	72.0%
F2	33.8%	59.3%	70.5%	60.0%	84.0%	92.0%
F3	21.0%	37.9%	47.4%	27.0%	61.0%	68.0%
F4	14.6%	30.9%	40.8%	23.0%	43.0%	63.0%
F5	36.9%	58.9%	68.4%	27.0%	55.0%	65.0%
F6	25.5%	54.6%	67.2%	53.0%	78.0%	86.0%
F7	24.7%	49.2%	61.8%	47.0%	73.0%	82.0%
F8	25.3%	50.7%	60.2%	39.0%	68.0%	76.0%
F9	36.9%	63.1%	75.4%	36.0%	66.0%	78.0%
F10	39.2%	61.4%	71.3%	52.0%	83.0%	89.0%
F11	34.0%	57.1%	69.4%	51.0%	85.0%	92.0%
F12	45.3%	72.1%	81.4%	47.0%	77.0%	85.0%
F13	27.8%	49.4%	58.2%	37.0%	71.0%	82.0%
F14	41.2%	63.9%	74.0%	38.0%	68.0%	81.0%
F15	42.2%	68.6%	76.1%	37.0%	64.0%	82.0%
F16	32.1%	58.7%	71.9%	55.0%	84.0%	88.0%
F17	31.5%	60.2%	70.7%	52.0%	83.0%	87.0%
F18	42.8%	69.9%	81.4%	46.0%	78.0%	86.0%
F19	28.6%	54.0%	66.2%	45.0%	75.0%	85.0%
F20	41.0%	66.8%	77.5%	47.0%	76.0%	85.0%
F21	39.1%	67.8%	77.1%	40.0%	72.0%	84.0%
F22	37.1%	63.3%	72.8%	59.0%	84.0%	92.0%
F23	49.9%	74.0%	81.8%	52.0%	83.0%	90.0%
F24	47.8%	75.2%	81.0%	50.0%	80.0%	91.0%
F25	45.3%	70.3%	77.7%	42.0%	74.0%	86.0%
F26	34.0%	63.7%	72.5%	60.0%	83.0%	90.0%
F27	46.4%	72.1%	80.8%	55.0%	82.0%	91.0%
F28	44.7%	71.9%	81.4%	52.0%	82.0%	89.0%
F29	42.0%	68.8%	78.1%	51.0%	78.0%	88.0%
F30	49.2%	75.9%	81.8%	54.0%	85.0%	92.0%
F31	46.5%	72.7%	80.6%	55.0%	84.0%	90.0%
CMC <sup>top</sup>	<b>57.1%</b>	<b>76.9%</b>	<b>84.9%</b>	<b>68.0%</b>	<b>86.0%</b>	<b>93.0%</b>
CMC <sup>triplet</sup>	<b>57.5%</b>	<b>77.7%</b>	<b>84.3%</b>	<b>69.0%</b>	<b>87.0%</b>	<b>92.0%</b>

multiple low-level visual features into a single framework. The approaches are generalized and adaptive to different person re-id datasets by automatically discovering the effects of visual features in recognizing persons. Extensive experimental studies demonstrate that our approaches advance the state-of-the-art results by a significant margin. Our framework is practical to real-world applications since the performance can be concentrated in the range of most practical importance. Moreover our approaches are flexible and can be applied to any metric learning algorithms. Future works include incorporating depth from a single monocular image [24], integrating person re-id with person detector [32] and improving multiple target tracking of [28] with the proposed approaches.

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**Table 9:** Comparison with different metric learning algorithms against varied PCA dimensions.

Algorithm	VIPeR	iLIDS	CUHK01
KISSME (32,100)	34.8%(28.5%, 28.6%)	53.3%(50.0%, 53.3%)	25.5%(19.3%, 25.5%)
LMNN (32,100)	28.2%(24.7%, 28.1%)	42.9%(39.8%, 42.9%)	24.0%(18.7%, 24.2%)
LDML (32,100)	27.8%(24.1%, 28.0%)	42.4%(38.0%, 42.3%)	23.9%(18.1%, 23.8%)
CMC <sup>top</sup> (32,100)	35.4% (33.2%, 35.4%)	67.1% (54.1%, 67.2%)	30.7% (26.4%, 30.7%)

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